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Gearbox Health Condition Monitoring: A brief exposition

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Abstract: Gearbox is a mechanical power transmission device, most commonly used to get the mechanical benefits in terms of speed and torque. The gearbox is made up of different types of gears assembled in a cascading order to perform the intended task. Failure of any rotating component inside the gearbox will terminate the working condition of the mechanical system associated with it. This causes interrupted services to the industries, which lead to expensive compensation. Especially, in an aircraft engine, it is used as an accessory drive, which provides power for hydraulic, pneumatic and electrical systems. This motivated to monitor the gearbox health condition. This paper presents a brief review of GHCM (gearbox health condition monitoring), gearbox faults, overview of time-domain features, frequency-domain features, time-frequency domain; feature extraction techniques, and fault classification techniques. The outcome of this study is to provide brief information regarding gearbox health condition monitoring.

Keywords: Gearbox faults, GHCM, Fault classification techniques.

1. Introduction

Gearbox is an accessory drive, which forms a part of the aircraft gas turbine engine. The accessory gearbox provides power for hydraulic, pneumatic and electrical systems. It drives fuel pumps, oil pumps, and tachogenerator. The accessory gearbox is coupled to the high-pressure compressor through radial drive shaft and power required for the gearbox is taken from the central shaft linking the turbine and high-pressure compressor sections of the engine. The power for the accessory units is drawn from the rotating engine shaft to an external gearbox through the internal gearbox, which provides motion for the accessories and distributes the accessory gear drive to each drive unit [1]. Figure 1 shows the location of gearbox mounting in an aircraft engine. In some early engines, the radial shaft is used to drive each accessory units. Although it provides the flexibility of placing accessory units in desirable units, it decreases the individual gear power transmission. It necessitated to the use of the large internal gearbox. The location of the internal gearbox is complicated due to the availability of small space between high-pressure compressor outlet and combustor. The thermal expansion and reduction in engine performance due to the mounting of the internal gearbox and radial drive shaft (disturbing the flow of gas), create major problems in the turbine area than the compressor area. For any given gas turbine engine, the turbine area is smaller than that of the compressor, which makes it easier to mount the gearbox within the space provided in a compressor physically. The main use of a radial drive shaft is to transmit the driving power from internal gearbox to external gearbox. It can be vice versa also i.e. to transmit the high starting torque from the starter to high-pressure compressor system for engine starting purposes. It is desirable to have the smallest drive shaft diameter to reduce the airflow disruption. The smaller the diameter, the faster the shaft must rotate to produce the same power. However, there is a limitation to this diameter as it increases the internal stress and adds greater dynamic problems, which result in vibration. The usage of intermediate gearbox depends on the design of the engine structure and its size. The intermediate gearbox is assembled between the internal gearbox and external gearbox when there is no provision for direct linking of the radial shaft to the external gearbox. The external gearbox provides a mounting face for each accessory unit and consists of drives for accessories. The location of the external gearbox depends on several factors. It is wrapped around the low frontal area of the engine in such a way to reduce drag effect while the aircraft is flying and as it is in the lower part, it is easy to access for maintenance people. If any accessory unit fails, stopped from rotating, it could cause failure to the other units. To avoid such secondary failure, the accessory unit driveshaft is designed like a shear neck, which is designed to fail if it incurs stress of one-fourth more than normal maximum load. Only the defective unit is isolated from the operation. When the accessory drive is drawn from two compressor shafts, two external gearboxes are required to be mounted on the top and bottom of the engine designed specially as 'low speed' and 'high speed' external gearboxes. When the design of engine and airframe does not provide enough space to accommodate all the accessory units on a single external gearbox, the auxiliary gearbox is a convenient method to provide additional accessory drives. The drive is taken from the external gearbox to auxiliary gearbox as similar from internal gearbox to the external gearbox.

This paper presents a brief review of gearbox health condition monitoring that includes the description of gearbox faults, gearbox datasets, workflow of gearbox health condition monitoring – sensors, pre-processing, feature extraction techniques followed by fault classification techniques.

2 Gearbox Faults

The failure of gearbox can cause a rotating machinery to breakdown, which leads to expensive repair and delay in work to be performed. The following are the different types of faults that occur in the gearbox [2-4].

2.1 Gear Misalignment

It makes the normal rotation of the gears more difficult as the misaligned gear area has no mating contact of gear teeth. This causes a slowdown of the rotation, which further adds more friction in the rotation, resulting in overheating.

2.2 Gear Wear

The effective operation of the gearbox is reduced due to gear wear. The different types of identified gear wears are:

- Moderate wear: which leaves the contact patterns on the metal in the addendum and dedendum area of gear
- Excessive wear: it will cause a problem until a significant amount of material has been affected on the surfaces (pitting phenomenon can be observed on the gear surface with excessive wear)
- Abrasive wear: observed as removal of material from the mating surface due to heavy load or foreign material in the lubrication or metallic impurities of bearing in the lubrication
- Corrosive wear: due to continuous friction, the oil loses its dielectric property and breakdown occurs. The chemicals that exist in the lubricant attack the surface causing deterioration of the metallic surface and results in pitting.
- Frosting: it usually occurs in the dedendum area of the driving gear (many micro pits on the surface)
- Spalling: shallow pits on the surface which makes the gear face non-uniform
- Pitting: it is a form of localized corrosion that results in the formation of small holes in the metal
- Breakage: the removal of the entire tooth or piece of tooth from its body

2.3 Overload on Tooth

The contamination of lubrication oil is one of the reasons to experience overload on gear tooth. It further results in overheating causing smell and noise from the gearbox. If the load is continued to be applied further without proper monitoring, it may result in breakage of the gear tooth. The gear load affects the gear mesh frequency (GMF) and harmonics.

2.4 Gear Eccentricity

It is a typical manufacturing error, which cannot be sensed with the naked eye. After the gearbox installation, the failure of geometric integration between the gear train results in gear wear and overheating phenomenon [5]. It will reduce the lifespan of working gearbox resulting in abnormal noise and further failure.

2.5 Excessive Backlash

Backlash is defined as the mating clearance between the gear teeth. They reduce the speed of gear meshing, providing sufficient space for lubricating oil between the teeth. The desired backlash prevents overheating and tooth damage. Backlash allows heat expansion. As the gear starts rotating, they produce friction and heat. Due to this, the gears dimension expands and the clearance between gear tooth reduces and further increase in friction and overheating results in breakage of the tooth. Excessive backlash can cause gear noise (whirring, clunking). The excessive backlash excites the natural frequency of the gear causing uncertain frequencies to appear. They are represented as resonant frequencies of gear in the spectrum.

2.6 Oil Leakage and Debris in Oil

The smooth operation of the gearbox is ensured by oil, providing lubrication for the gears and other components. If the mounting of gaskets and sealing is not proper, the oil leakage happens and reduces the lifespan of gearbox due to lack of sufficient lubrication. Presence of foreign material in the oil also causes friction between the mating contacts of gears and gear tooth faces. Further results in breakage of gear tooth due to overheating. Frequent maintenance should be conducted to check the oil level and oil debris detection. Oil debris in the lubricating system produced from the damaged component can cause failure of the gearbox, which is irreversible. Oil debris chip detectors can be used to monitor the freshness of oil in the gearbox. Oil debris analysis [6] is essential to measure the rotating machinery life effectively. When machine components begin to deteriorate (wear), the effect can usually be reflected in the lubricant passing through the machine. For example, as parts undergo sliding, fatigue or creep, pieces of metal will begin to break off the components and show up as wear debris in the lubricant. Traditionally, oil debris samples are taken to the lab to perform complete diagnostic tests on the lubricant, which is time-consuming and not transparent. In earlier days, real-time wear (foreign material) debris analysis tools become available, which help the maintenance personnel to detect changes in a machine's condition immediately and repair the damaged component before catastrophic failure [7].

2.7 Hunting Tooth Frequency

The hunting tooth frequency is defined as the rate at which a tooth in one gear mates with a particular tooth in the other gear. During the normal rotation of gears, once a while the two teeth will enter the mesh area concurrently and contact one another.

Table 1 shows the FFT spectral analysis of different gearbox faults. The behavior of the above faults is shown in terms of spectral components such as gear mesh frequency, residual signal - amplitudes, and sidebands. From the table, it can be inferred that the presence of a residual signal is shown only in excessive backlash, gear wear, and hunting tooth frequency.

3. Gearbox Health Condition Monitoring (GHCM)

The information flow cycle of gearbox health condition monitoring is shown in Figure 2. Sensors are used to acquire the data (temperature or acoustic or vibration data) from the gearbox. Then the raw data from the sensor is pre-processed to de-noise the signal. These pre-processed signals are processed to get time or frequency or time-frequency domain features. Then the computed features are classified to detect and diagnose the faults of the gearbox using feature classification techniques such as support vector machine.

Gearbox Datasets

The gearbox datasets that are available in the open literature for developing and testing the gearbox fault diagnosis and prognosis algorithms are given below.

UCI Machine Learning repository: This dataset consists of healthy and broken tooth cases of the gearbox. The vibration data was acquired from four accelerometer sensors mounted radially to the gearbox in four different directions. The datasets also include varying load from 0 to 90 [8].

NREL: National Renewable Energy Laboratory provided this dataset from wind turbine mechanism. The dataset consists of healthy and damaged vibration data with 1-minute duration of 8 sensors mounted in different locations surrounding the gearbox. Data were collected by using a dynamometer test facility at a sampling frequency of 40 kHz per channel [9].

Mechanical Dataset: This gearbox dataset is provided by Southeast University, China. The dataset includes bearing and gearbox faulty data. The data was collected under two loading conditions with rotating speed and load configuration set to be 20-0 and 30-2. Each file consists of 8 signals, 1-motor vibration, 2, 3, 4-vibration data of planetary gearbox along x, y, z directions respectively, 5-motor torque, 6, 7, 8-vibration data of parallel gearbox along x, y, z directions respectively [10].

5.1 Sensor

The following are the different types of sensors used in condition monitoring of rotating machinery [11].

5.1.1 Temperature Sensors

Thermal techniques are used to detect all types of defects in mechanical and electrical equipment if the defect is characterized by an increase in temperature. There are two types of temperature sensors, which are most commonly used. They are resistance thermometer and an infrared camera. Each sensor has its own importance of application based on location. However, the limitation of temperature sensors is, only surface thermal fluctuations will be detected by thermal imaging.

5.1.2 Acoustic Sensors

Acoustic emission (AE) is a phenomenon of sound that measures the stress wave frequencies, which are higher than those monitored by traditional vibration techniques. The frequency of operation ranges from hundreds of kHz to greater than 1MHz. Such type of signals are created by cracks, fiber breakage and removal of outer covering in composites or by impact. Crack growth, plastic deformation development, de-bonding and fracture can be detected using AE. Piezoelectric sensors with elements made up of ceramic materials like lead zirconate titanate, Ultrasonic and Microphone are some of the devices used as acoustic sensors. Acoustic sensors capture the mechanical movement (cracks) in the metal and converts into electrical signal. Environment variations may affect the operation of the acoustic sensors and lead to false interpretation. Therefore, analyzing the signal using acoustics is not a recommended method.

5.1.3 Vibration Monitoring Sensors

The vibration analysis is the most widely used condition-monitoring technique that can be applied to all types of rotating components such as gas turbines, generators, gearboxes, drivetrains and aircraft engines, etc. The vibration signals is used in the diagnosis of rotating machinery as they provide more numerical information compared with thermal and acoustic signals. When the machine is in rotating motion, these components generate characteristic vibrations whose frequency is regulated by the systems speed and geometry and their association with other parts. The magnitude of the vibration signal at a particular frequency is estimated but it will rise as wear or fault occurs and these changes in magnitude are used to detect the initiation of forthcoming failure. Several data processing techniques are applied to vibration signals, especially when mechanically complex equipment such as gearboxes are involved. The sensor that is characterized based on displacement, velocity and acceleration are used for vibration measurement. The choice depends on the application. Accelerometers are the most commonly used sensors to measure the vibration signal.

5.2 Preprocessing Filters

The vibration signal is preprocessed to de-noise the signal from unwanted residual signals. The preprocessing of the signal improves the diagnosis of the fault. The common filters used to de-noise the signal are Moving average filter, Auto-regressive filter, Kalman filter, Low pass filter, High pass filter, Band pass filter, and Band stop filter. In general, these filters are used in combination to preprocess the input signal.

5.3 Feature Extraction

Feature extraction is a dimensionality reduction technique, where an initial set of raw data is reduced into features that completely describe the original data set. When the input data to load into an algorithm is too large to be processed and if it consists of redundant variables, then it can be reduced into a set of features. Further, determining the useful features from the computed features is called feature selection. The selected features are expected to contain the relevant information that is used to perform the desired task of dimensionality reduction. The feature extraction techniques are classified into three categories as follows:

5.3.1 Time Domain Features

The time domain analysis examines the time versus amplitude characteristics of a measured signal. The statistical features [12-24] that can be extracted from the raw signal are: Mean, Median, Mode, Range, Interquartile range, Standard deviation, Variance (Hjorth's Activity), Co-variance, Root mean square (RMS), Root sum of squares (RSSQ), Root value, Maximum value, Peak to Peak, Crest factor, 'Moment' of order up to 5, Skewness, Kurtosis, Mean absolute deviation, Absolute mean value, Shape factor or Waveform factor, Impulse factor, Clearance factor or Margin factor or Latitude factor, Skewness factor, Kurtosis factor, Zero crossing, Waveform length, Willison amplitude, Slope sign change, Simple sign integral or Energy, Energy operator, Entropy, Hjorth's mobility and Hjorth's complexity. Apart from feature extraction, the time domain techniques used to manipulate the raw signal and analyze are: Time synchronously averaged (TSA) signal, Residual Signal, Difference signal, Band pass mesh signal and Empirical mode decomposition (EMD). The features extracted from these techniques are FM0, NA4, NA4* or ENA4, FM4, M6A, M8A, and NB4. The EMD [25-26] decompose the non-linear and non-stationary time series data into intrinsic mode functions (IMF) with decreasing order of frequencies.

5.3.2 Frequency Domain Features

Frequency domain analysis converts the measured signal (composite signal) into a group of sinusoidal signals which, when added together, produce the original waveform. The relative amplitudes, frequency, phases of sine waves are examined in the frequency domain. The frequency domain techniques used to extract the features from the signal are Fourier spectral analysis, Welch spectral estimation [27] and Multitaper spectral estimation [28]. The features [29] that can be extracted in the frequency domain are: Mean frequency, Frequency center, Root mean square frequency (RMSF), Root variance frequency (RVF), Coefficient of variability, Stabilization factor of wave shape, Spectral skewness and Spectral kurtosis.

5.3.3 Time-Frequency Response Analysis

Time-frequency response is a prospect of the signal represented over both time and frequency. As we know the main limitation of time domain analysis is noise and disturbances are removed from the original signal (approximation) and the Fourier transform has some restrictions, i.e., the system should be linear and the data must be periodic or stationary. Even though many natural phenomena can be approximated to linear systems, they will also have the tendency to be non-linear whenever the variations become finite amplitude. The interactions of the imperfect probes even with a perfectly linear system can make the final data non-linear. In general, the available data is of finite duration, non-stationary and non-linear. Under these conditions, the Fourier spectral analysis is of limited use. The vibration signals from gearbox are characterized as non-stationary that leads to spectral smearing (damage the reputation by false accusations) during application of FFT based technique and creates uncertainty in the fault diagnosis. Signals measured on the gearbox will change as load change while traditional FFT spectral methods cannot be used. Therefore, to overcome the limitations in time domain and frequency domain techniques, time-frequency analysis has been evolved. The techniques used in time-frequency analysis are Short Time Fourier Transform (STFT), Wavelet transformations [30-31] and Wigner Ville Distribution (WVD).

5.4 Fault Classification Techniques

Fault classification is one of the important issues to be considered to diagnose the faults in the rotating machinery. After the detection of a fault by analyzing the extracted features, it is necessary to classify the type of fault. The most frequently used fault classification techniques are Support Vector Machine (SVM), Artificial Neural Network (ANN), k Nearest Neighbor (kNN), Hidden Markov Model (HMM), Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Naïve Bayes Classifier, Random Forest Regression, Boosting Tree Regression and Classification and Regression Test (CART). Table 2 shows a brief illustration of classification techniques [32-39].

5.5 Fault Diagnosis & Prognosis

The type of fault and location is detected using a suitable classification technique and predictive model. The remaining useful life (RUL) estimated from the predictive models is used for the cost-effective operation of rotating machinery. From the prognosis data, preventive failure actions are implemented the maintenance personnel. Therefore, the gearbox health condition monitoring is a continuous process to achieve uninterrupted service of the mechanical system with less maintenance.

6. Conclusion

In this paper, an attempt has been made to understand the importance of gearbox in the aircraft engine and the approach followed to monitor the gearbox health condition. Different types of faults that occur in the gearbox and their characteristic behavior are also discussed. The sequence of operations to be performed in the gearbox health condition monitoring is presented. This paper also presents the gearbox datasets (resources), sensor devices used for acquiring the signal, an overview of feature extraction techniques and feature classification techniques to detect and diagnose the gearbox faults. The future work of this paper is to analyze the gearbox health condition using the available gearbox datasets and proposed information flow diagram.

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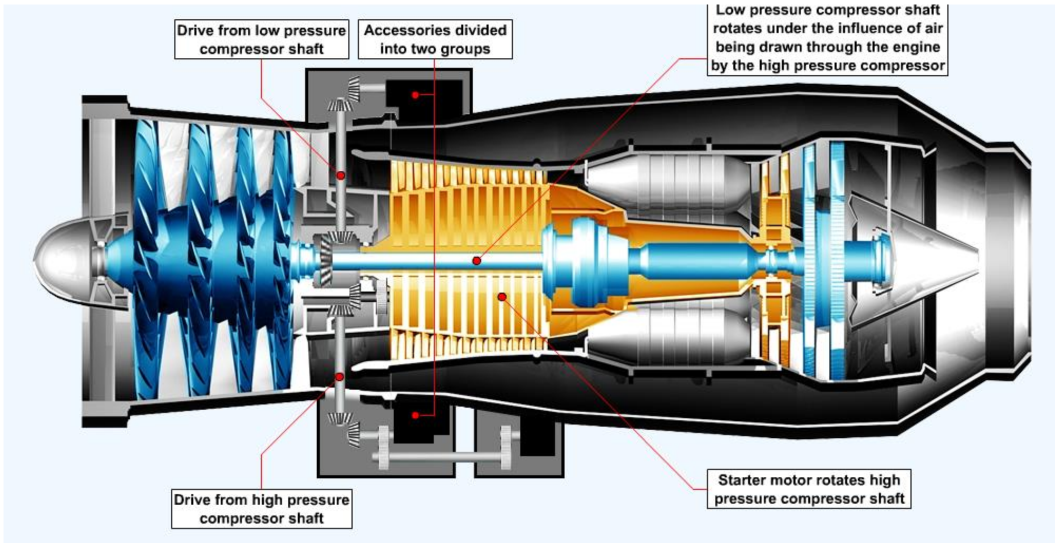

Figure 1 Gearbox mounting in gas turbine engine; (Source: 40. https://gas-turbines.weebly.com/gear-boxes--accessory-drives.html.)

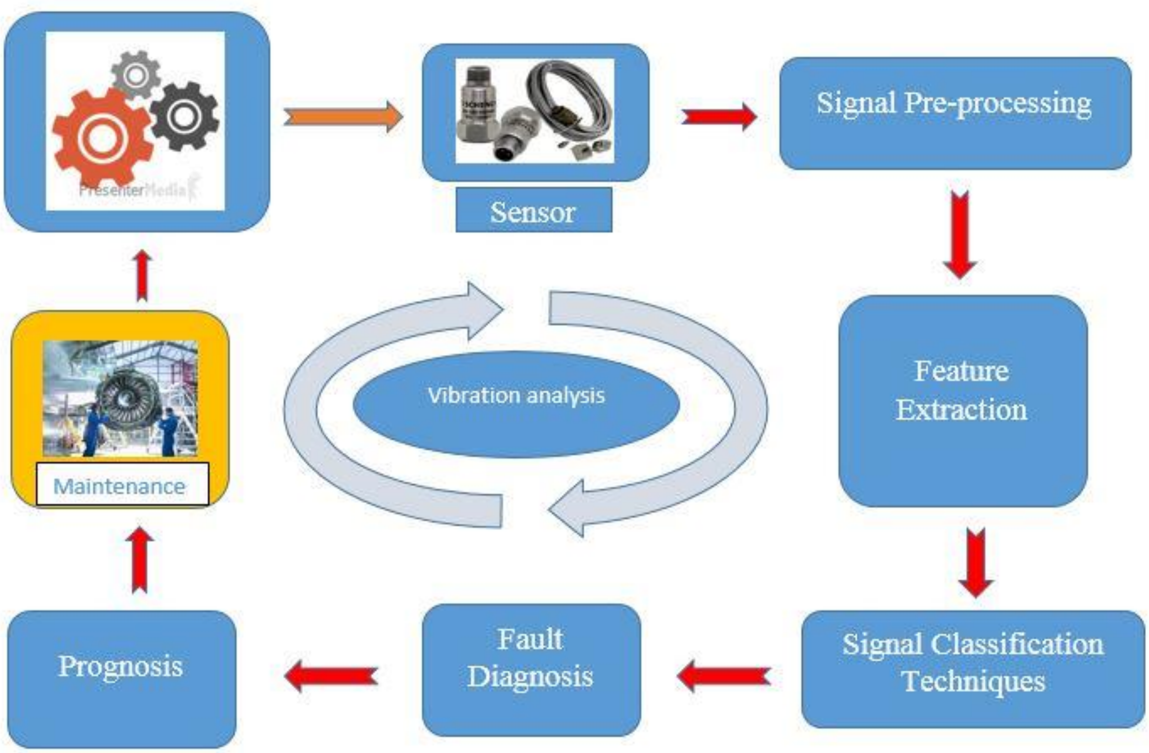

Figure 2 Information flow cycle of GHCM

Table 1 FFT response to gearbox faults

Gear Faults	Symptoms (Spectrum)											
	GMF		2xGMF		3xGMF		Residual Signal		Output Rpm		Pinion Rpm	
	A	SB	A	SB	A	SB	A	SB	A	SB	A	SB
Normal Gear Spectrum	—	—	↓	✗	↓	✗	✗	✗	—	✗	—	✗
Gear Misalignment	—	—	↑	↓	↓	↓	✗	✗	—	↑	—	↑
Gear Eccentricity	↑	↑	↑	↑	↑	↑	✗	✗	—	✗	↑	✗
Excessive Backlash	↑	↑	↑	↑	↑	↑	✓	✓	—	✗	—	✗
Gear Wear	↑	↑	↑	↑	↑	↑	✓	✓	—	✗	—	✗
Gear Load	↑	↓	↓	↓	↓	↓	✗	✗	—	✗	—	✗
Hunting Tooth Frequency	—	—	✗	✗	✗	✗	✓	✓	—	↓	—	↓

Note: A = Amplitude, SB = Sidebands, GMF = Gear Mesh Frequency, '—' = Normal, '✗' = Not Present, '✓' = Present, '↓' = Decreased Amplitude, '↑' = Increased Amplitude.

Table 2 Brief illustration of classification techniques

Sl. No.	Classification Techniques	Type	Application	Remarks
1	Support Vector Machine (SVM)	Supervised MLA	Feature classification or regression	N-dimensional classification with two input feature vectors
2	k Nearest Neighbor (kNN)	Nonparametric method (MLA)	Classification or Regression (pattern recognition)	Overlapping of samples in some regions of feature space.
3	Artificial Neural Network (ANN)	MLA	Optimization problems	Stochastic behavior of the network
4	Hidden Markov Model (HMM)	Markov chain MLA	Predictive Analysis	The accuracy of classifier vary with the number of HMM states
5	Principal Component Analysis (PCA)	Dimensionality Reduction	Exploratory data analysis and predictive models	Unsupervised technique
6	Linear Discriminant Analysis (LDA)	Analysis of Variance	Pattern recognition	Non – Linear Problems
7	Naïve Bayes Classifier	Probabilistic classifier	Predictive models	The assumption on the shape of the data distribution
8	Random Forest Regression (RF)	Regression model	Recursively partitioning data models	Accuracy depends on the size of the model
9	Boosting Tree Regression (BT)	Regression model	Predictive models	Needs at least two predictor variables to run
10	Classification and Regression Test (CART)	Tree algorithm	Predictive models	Overfitting and biased toward predictors with more variance

Note: MLA = Machine Learning Algorithm